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A review and framework of control authority transitions in automated driving

Zhenji Lu*, Joost C.F. de Winter

*Department of BioMechanical Engineering, Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology,
Mekelweg 2, 2628 CD Delft, The Netherlands*

Abstract

The paper reviews some of the essentials of human-machine interaction in automated driving, focusing on control authority transitions. We introduce a driving state model describing the human monitoring level and the allocation of lateral and longitudinal control tasks. An authority transition in automated driving is defined as the process of changing from one static state of driving to another static state. Based on (1) who initiates the transition and (2) who is in control after the transition, we categorize transitions into four types: driver-initiated driver control (DIDC), driver-initiated automation control (DIAC), automation-initiated driver control (AIDC), and automation-initiated automation control (AIAC). Finally, we discuss the effects of human-machine interfaces on driving performance during transitions.

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1. Introduction

Automated vehicles have recently drawn a great deal of attention. Technology companies, such as Google, as well as vehicle manufacturers, such as Nissan, Mercedes, BMW, and Volvo, are testing their automated driving products or prototypes on public roads. These developments follow up on various advanced driver assistance systems (ADAS) that have been introduced in the last three decades, including Anti-lock Braking Systems, Collision

* Corresponding author. Tel.: +31 (0)15 278 78 91.
E-mail address: Z.Lu@tudelft.nl

Warning Systems, Adaptive Cruise Control (ACC), Lane Keeping Assistance (LKA), and Automatic Parking. Experimental research as well as field operational tests have demonstrated that ADAS can not only improve traffic efficiency and cut down fuel consumption but also reduce traffic accidents[1], of which over 50% are primarily caused by unintentional human error[2,3].

Several general conclusions can be derived from previous research on human-machine interaction: a greater degree of automation generally reduces the variability of human performance, but on the other hand leads to ‘human-out-of-the-loop’ problems, such as complacency, loss of situation awareness, loss of manual control skills, and behavioral adaptation [4–7]. A literature review by De Winter et al. [8] showed that drivers’ workload and situation awareness are vastly different for driving with ACC compared to Highly Automated Driving (HAD). Such human factors issues resulting from increased automation levels need to be taken into consideration when designing automated vehicles [9,10].

Sooner or later, fully automated vehicles without human supervision will be on the roads. However, at present, many problems of technology and legalization still need to be solved, and peoples’ opinions are divergent regarding the desirability of fully automated vehicles[11]. Before the moment of fully automated vehicles arrives, drivers will have to supervise their automated cars. That is, due to functional limitations of automation, hardware failure, or policy factors, drivers may have to resume manual control at certain moments during their drives. Such control authority transitions in automated driving need to be studied, especially when considering that human factors research over the past decades has repeatedly demonstrated that humans are not good at supervisory tasks [12]. Driving simulator research which has studied human behavior during authority transitions in automated driving has shown that accidents and near-accidents are likely to occur if humans suddenly have to resume manual control [13–16].

This review will begin with introducing the fundamental concepts of levels and stages of automation. By comparing different definitions of levels of automated driving, key principles of authority transitions are extracted. Accordingly, a driving state model is introduced. Next, a categorization tree is introduced that identifies different types of transitions and which can be used to cluster transition scenarios. Finally, we discuss the importance of a human-machine interface (HMI) for safe transitions.

2. Transitions defined as changes in primary functions: monitoring and control

Automation systems can be described across four stages: 1) information acquisition; 2) information analysis; 3) decision and action selection; and 4) action implementation [17]. Bainbridge [18] argued that ‘monitoring’ and ‘taking over control’ are the two primary tasks that are left for human operators when using an automated system. These primary tasks resemble the stages of automation defined by Parasuraman et al. [17], where monitoring corresponds to information acquisition and analysis, and control of lateral and longitudinal directions corresponds to decision-making and action implementation.

2.1. Levels of automation in automated driving

The German Federal Highway Research Institute (BAST), the Society of Automotive Engineers (SAE), and the National Highway Traffic Safety Administration (NHTSA) have each created their definitions of ‘levels of automated driving’ [19–21]. Although these definitions vary, the essential criteria that define the different levels of automation are similar in each of the three cases. These essential criteria refer to how the primary functions (i.e., monitoring and control) are distributed between the human and the automation.

For example, the difference between Assisted Driving (AD) and Partially Automated Driving (PAD) as defined by BAST is that in PAD, the automation takes over both lateral and longitudinal control, while only one of these is controlled in AD. This distinction between AD and PAD is equivalent to the distinction between Driver Assistance and Partial Automation in the SAE definition, and equivalent to the distinction between ‘Level 1 Function-Specific Automation’ and ‘Level 2 Combined Function Automation’ in the NHTSA definition. Furthermore, the BAST definition states that the difference between PAD, HAD and Fully Automated Driving is the required monitoring frequency which decreases from ‘permanently’ in PAD, ‘need not permanently’ in HAD, to ‘need not’ in

'Fully

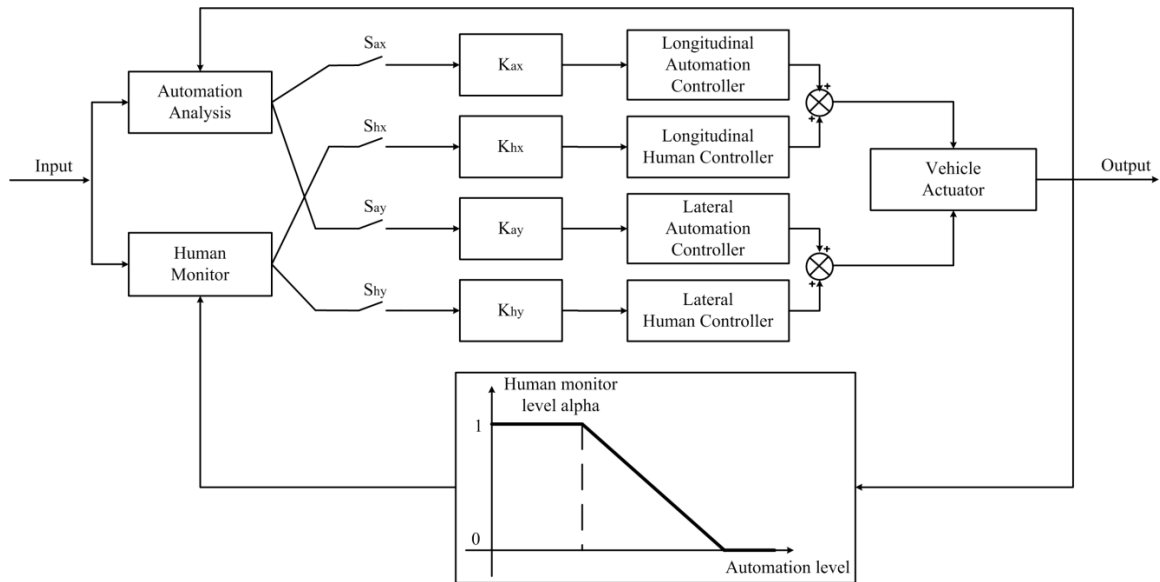


Fig. 1. Control diagram illustrating the states of automated driving. hx = human longitudinal; hy = human lateral; ax = automation longitudinal; ay = automation lateral. The human monitor level alpha changes with as a function of the driving state, as explained in the text.

Automated Driving (FAD). This monotonic decrease of monitoring frequency with increasing level of automation can also be identified in the SAE and NHTSA definitions of levels of automated driving.

2.2. Driving states in automated driving

A transition can be defined as a period in which the system changes from one state to another state [22]. States of automated driving systems are defined in a more fine-grained manner than the aforementioned levels of automation. For example, systems with only lateral support or only longitudinal support are classified as the same level of automation in the definitions provided by BAST, SAE, and NHTSA, even though human workload and situation awareness are known to be different during lateral support as compared to during longitudinal support [23]. Defining authority transitions in terms of states does not only integrate the different definitions of levels of automated driving, but can also be used to distinguish between the possible modes of function allocation. The control diagram representing the states of automated driving is illustrated in Figure 1.

In Figure 1, *Input* is information regarding the planned trajectory, states of the vehicle (such as velocity and acceleration), and environment information (such as traffic signs and other vehicles). *Output* is the actual vehicle trajectory and the states of the vehicle. (S_{ax} , S_{hx}) and (S_{ay} , S_{hy}) are two pairs of switches that allocate control authorities in the longitudinal and lateral directions. If one assumes static states, only one switch is turned on in each pair of switches. (K_{ax} , K_{hx}) and (K_{ay} , K_{hy}) are two pairs of adaptive parameters that are used to tune the control weights of human and automation. These parameters are set to 1 in the case of static states. However, these variables can optionally be tuned in the case of dynamic states in which both switches can be turned on at the same time (e.g., to facilitate the concept of 'shared control' [24]).

The 'human monitor' (a biological agent) and 'automation analysis' (a computer agent) acquire and analyze the input and output information, make decisions, and feed signals to the longitudinal and lateral human or automation controllers. The longitudinal and lateral automation controllers are transfer functions that generate control signals, such as steering and pedaling signals. The vehicle actuator will implement these directional signals to move the

vehicle. The output will be feedback to the ‘automation analysis’ directly. The human monitor level ‘alpha’ represents the required human monitoring frequency. The ‘human monitor level function’, which determines how much output information will be fed back to the ‘human monitor’ is represented by ‘alpha’. If the driver does not need to monitor, alpha is set to 0; on the contrary, alpha is 1 when the driver is required to monitor permanently.

The static states are listed below.

- *State 1*: if S_{hx} and S_{hy} are both switched on, and S_{ax} and S_{ay} are both switched off, then the state is manual driving, where alpha needs to be 1.
- *State 2.1*: if S_{ax} and S_{hy} are both switched on, and S_{hx} and S_{ay} are both switched off, then the state represents driving assistance with longitudinal support (like ACC). Here, alpha still equals 1, because the driver is engaged in other control tasks.
- *State 2.2*: if S_{hx} and S_{ay} are both switched on, and S_{ax} and S_{hy} are both switched off, then this state represents driving assistance with lateral support (like LKA). Alpha equals 1, for the same reason as in State 2.1.
- *State 3*: if S_{ax} and S_{ay} are both switched on, and S_{hx} and S_{hy} are both switched off, then this state maps to partially automated driving with lateral and longitudinal support (like vehicles equipped with both ACC and LKA). The driver is still required to monitor permanently to be able to take over control anytime needed. Hence, alpha is still 1.
- *State 4*: If S_{ax} and S_{ay} are both switched on, and S_{hx} and S_{hy} are switched off, but unlike State 3, the driver does not need to monitor permanently, then this state corresponds to highly automated driving. This means that alpha floats between 0 and 1.
- *State 5*: If the conditions of the switches are the same as in State 3 and State 4, but the driver does not need to monitor (so alpha equals 0), then this state corresponds to fully automated driving.

State 2.1 and State 2.2 are both categorized within State 2, because both states belong to the same level of automation [19–21]. However, as we discussed above, the control task allocations in these two states are different from each other.

2.3. Definition of transitions

Based on the driving states above, transitions in automated driving can be defined as the process of changing from one static state of driving to another static state. Flemisch et al. [25] tried to include all transitions in one continuous spectrum of automation. We refine this spectrum, by pointing out the difference between monitoring transitions and control authority transitions. Transitions among States 3, 4, and 5 concern changes in the driver’s monitoring status. Control authority transitions, which refer to changes of allocation of control action, will occur when States 1, 2.1, or 2.2 are involved. The changes of monitoring level for some of the control authority transitions (e.g., monitoring level increases from 0 to 1 during the transition from state 5 to state 1) are not emphasized, because the responsibility of monitoring is driven by the control authority [22].

Figure 2 illustrates the overall concept. Solid lines represent control authority transitions, while dotted lines represent monitoring status transitions. A control authority transition in automated driving is defined as a process where control authority changes from one static state of driving into another static state. Therefore, the changes of authority of lateral, longitudinal, or both control tasks, are referred to as control authority transitions.

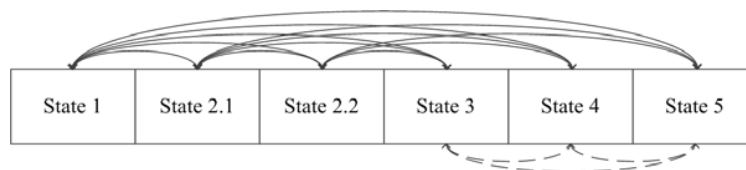


Fig. 2. Transitions between different states.

3. Categorization of control authority transition in automatic driving

Prior research indicates that *who* (human or automation) should initiate a transition is an essential topic in the design of adaptive automation and function allocation in general [26–28]. Flemisch et al. [22] argued that control authority transitions in automation systems should depend on the abilities of both human and automation. In other words, before changing control authority in a particular situation, the agent (either human or automation) who initiates the transition should have knowledge of the momentary driving capabilities of the other agent.

3.1. Categorization of transitions

In automated driving, two main transition categories are driver-initiated transitions and automation-initiated transitions. Each of these two main categories can be divided into two subcategories: ‘driver in control’ and ‘automation in control’, referring to who is in control after the transition has occurred. The corresponding categorization tree is shown in Figure 3.

3.2. Scenarios in each transition categories

In driver-initiated transitions (DIDC & DIAC), the driver usually has some time to prepare the transition. Both the DIDC and DIAC transitions can be triggered based on the driver’s preference of control while he or she is judging one’s own driving fitness and the capabilities of the machine. A DIDC can also be triggered by an automation failure; the driver, who notices this failure, subsequently initiates the transition.

In the case of a transition initiated by the automation (AIDC & AIAC), the automation should have sufficient information to make this decision. AIDC transitions may be caused by automation limitations or by a computer failure detected by on-board diagnostics. Another possibility is that the automation adaptively hands over control to raise driver situation awareness or to solve other human-out-of-the-loop problems. An AIAC transition does not imply that the automation should overrule the human. We recommend that automation should not make decisions and implement actions without human consent, except in cases where, through inaction, the human will get hurt (similar to Isaac Asimov’s laws for robotics[29]). For example, when a driver fails to drive safely during a heart attack, the automation needs to take over control if it can. AIAC transitions may also occur when humans are (legally) required to hand over transitions. For example, in future intelligent traffic consisting of platoons of automated vehicles [30,31], entering a platoon may require an AIAC transition to let the host vehicle cooperate with other vehicles and infrastructure automatically.

DIDC and AIAC are active transitions, because whoever initiates the transition is usually prepared to take over control afterwards. In contrast, DIAC and AIDC are passive transitions, because whoever is in control after the transition is forced to take over control from the other agent. Thus, lack of preparation in passive transitions may lead to unsafe situations. In DIAC, the driver is in the loop before the transition, and he/she may be expected to be aware of the automation modes and driving environment. As for AIDC, if drivers cannot respond properly, the transition could lead to a serious accident. This may explain why most transition scenarios in driving simulator experiments belong to the AIDC category. The most common AIDC scenario can be summarized as follows: due to

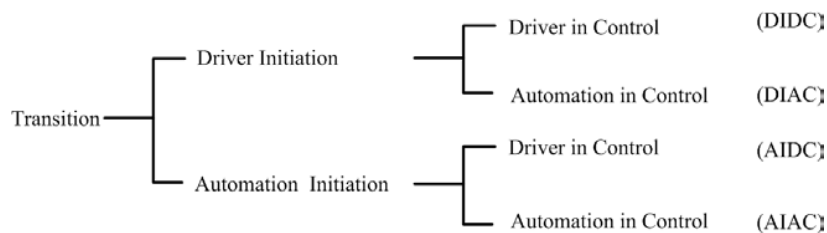


Fig. 3. Categorization tree of control authority transition.

an automation limitation (e.g., the automation detects an accident in front of the host vehicle and cannot cope with this situation), participants are warned, such as through a visual-auditory signal, to take over control by braking or steering within a set time margin [32–36]. Other AIDC scenarios have also been tested in driving simulator studies, including, for example, multiple lanes reducing to a single lane [15]. Besides AIDC transitions, some DIDC transitions have also been tested in driving simulator research. For example, in some studies, the automation failed to detect a traffic sign or obstacle, and the driver was expected to react to this simulated sensor failure [37].

Setting up scenarios is a challenge in experimental research, because theoretically everything is possible regarding future technologies. However, we recommend that experimental design in human factors research should investigate scenarios that are ‘reasonable’, taking into account our proposed categorization tree (Fig. 3). This categorization tree could provide guidance for designing scenarios with a theoretical basis.

4. Issues of HMI and control systems during transitions

Research shows that mental workload and situation awareness generally decrease with increasing levels of automation [5,16,38,39]. Furthermore, drivers’ reaction time often increases dramatically in automated driving conditions compared to manual driving[13].

A human machine interface(HMI), which enables the human to recognize the automation’s intentions and to perceive the automation’s limitations, may improve driver performance and reduce the human-out-of-loop problems[13,40,41].

Several studies have investigated the effect of take-over request time on the way drivers reclaim of the vehicle. Generally, it has been found that[15,32,37]:

- The higher the level of automation, the more time drivers need to re-obtain situation awareness and take over manual driving.
- The shorter warning time, the worse the take-over quality will be.

However, the results from different experiments vary due to various specific simulation conditions and different definitions of transition time. For example, Gold et al.[32] suggested that drivers need to be warned at least seven seconds in advance, in order for them to take over control safely. The conclusions were based on the measurement of driving performance, “hands on” time and “road fixation” time. In contrast, the results from experiments by Merat et al.[15], which focused on driver behavior *after* transitions, showed that drivers need around 40 s to resume and stabilize the control of the vehicle during the transition from NHTSA Level 3 Automation [20] driving to manual driving.

Additionally, take-over performance varies between different warning methods, such as between visual or auditory warning[42,43]. For example, Biondi et al. [42] showed that a ‘beep’ has a negative effect on driving performance as it distracts drivers. On the other hand, Naujoks et al. [43] stated that visual-auditory warning method can decrease drivers’ reaction times compared with a visual warning.

The transition control system is another important topic to be discussed. Nilsson [44] indicated that when drivers encounter an automation failure, they prefer to steer instead of applying the brakes. Similarly, Levitan et al. [45] found that drivers prefer to take over control from automation by first steering and then using accelerator, instead of vice versa. This implies that control systems should be designed to assign more weight to steering than to braking. The drivers’ transition performance for different initiation methods should be investigated empirically. The development of HMIs and controllers for smoothly and safely transferring control authority between automation and human is a major challenge for human factor researchers in automated driving.

5. Conclusion and discussion

In this review, we described static states of automated driving based on two primary tasks: control and monitoring. A transition in automated driving was defined as the process of changing from one static state of driving to another static state. Note that a temporary interruption of control without changing the actual state is not a

transition. For example, a driver providing a change of set-points during ACC driving without turning off the ACC should not be regarded as a transition.

Based on the definition of a transition, control authority transitions between different states were categorized into four categories: DIDC, DIAC, AIDC, AIAC. We note that when a transition occurs between state 2.1 and state 2.2, two types of transitions occur at the same time, because authority of both lateral and longitudinal control tasks change at the same time. Thus, if the automation engages a transition from LKA to ACC, then AIDC and AIAC transitions occur in lateral and longitudinal control, respectively. Whether transitions are time-critical or not is another important factor. We acknowledge that time criticality can potentially also be used to classify transitions. However, time is a continuous variable, making it hard to formally distinguish between emergency and non-emergency events during driving.

Previous research has discussed whether intermediate states are necessary during transitions. For example, shared control—defined as a situation where human and automation are carrying out tasks simultaneously—may be able to facilitate smooth control authority transitions [46–48]. However, more simple approaches, like gradually changing the control force, are another viable option [35]. Driving performance needs to be compared for different control systems in order to understand the pros and cons of each approach.

The function allocation can be achieved by the human driver and/or the automation controlling the two pair of switches: (S_{ax}, S_{hx}) , (S_{ay}, S_{hy}) , and optionally, by tuning the weight values: (K_{ax}, K_{hx}) , (K_{ay}, K_{hy}) . Previous research has demonstrated that *adaptively* allocating the functions between human and automation can be a beneficial approach [7, 49, 50]. For this purpose, a function allocation agent needs to be created that can allocate a set of tasks to both the driver and the automation, and which can determine whether transitions should happen under certain circumstances. The agent should not only consider the conditions of the environment and automation, but also be able to detect the states and habits of the driver. As Klein [51] demonstrated, humans tend to execute actions they have experienced before, instead of acting optimally in time-limited tasks. Hence, this pleads for an automatic switching agent as opposed to a human one.

Through training and experience, drivers can learn to work around automation problems. For example, as Larsson et al. [52] showed, when drivers get accustomed to ACC, they become more aware of the system's limitations and respond quicker to emergency situations. Nonetheless, automation designers need to understand the limitations of humans when they implement a high level of automation. Human errors cannot be eliminated by installing automation, since automation systems are designed by humans. This makes automation systems more vulnerable to the errors of designers [6, 53].

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